Remote Sensing of Environment 123 (2012) 347–358

Contents lists available at SciVerse ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Assessment of vegetation indices for regional crop green LAI estimation from Landsat images over multiple growing seasons

Jiangui Liu, Elizabeth Pattey *, Guillaume Jégo

Agriculture and Agri-Food Canada, 960 Carling Avenue, Ottawa, Ontario, Canada K1A 0C6

ARTICLE INFO

Article history:
Received 21 November 2011
Received in revised form 29 March 2012
Accepted 1 April 2012
Available online 3 May 2012

Keywords:
Green LAI
Landsat
Assimilation
Vegetation indices
Uncertainty
Agriculture
Sensitivity analyses
Corn
Wheat
Soybean

ABSTRACT

There is an increasing need to monitor the dynamics of green LAI of field crops through the growing season. A simple approach is to use a regression model to estimate crop LAI from a vegetation index derived from optical remote sensing data. However, variations of interference factors in the signal path could induce variations in spectral reflectance, leading to uncertainty in LAI estimation. A semi-empirical equation was implemented to estimate green LAI of field crops from Landsat-5/7 data using a few vegetation indices, including the normalized difference vegetation index (NDVI), the optimized soil adjusted vegetation index (OSAVI), the two band enhanced vegetation index (EVI2) and the modified triangular vegetation index (MTVI2). Data were collected during several growing seasons, from 1999 to 2006, over corn, soybean, and spring wheat fields in an experimental farm in Ottawa (ON, Canada). LAI estimated for corn, soybean and wheat from Landsat data using the vegetation indices was compared to ground LAI. Except for NDVI, comparable results were obtained from the other three vegetation indices, with a coefficient of determination above 0.83 and a root mean square error (RMSE) not more than 0.60. The performance of NDVI was less satisfactory (RMSE > 0.66). The uncertainties in LAI estimation induced by variations in soil reflectance, leaf optical properties, canopy structure, and atmospheric conditions were assessed through a global sensitivity analyses using the PROSPECT leaf model coupled to the SAIL canopy model along with the 6S atmospheric transmission model. The sensitivity analyses show that different indices are affected differently by the various interference factors. Comparatively, NDVI is the most influenced by leaf chlorophyll but the least affected by leaf inclination, OSAVI and the narrow band MTVI2 are more efficient in reducing soil effects, and EVI2 has a better performance in reducing aerosol perturbation. At high LAI, the uncertainty of NDVI is the smallest, but the uncertainty propagated to LAI estimation is the largest due to saturation. In this case, vegetation indices that are less prone to saturation should be considered, such as EVI2 and MTVI2. When MTVI2 is used on multispectral data, its ability to reduce soil and leaf chlorophyll perturbation is similar to EVI2 but weaker than when it is used on hyperspectral data. These results show that vegetation indices can be used in a simple regression model to generate baseline green LAI product for seasonal crop growth monitoring, however it is important to be aware of the sources of uncertainty and their relative amplitudes when using the product.

1. Introduction

Leaf area index (LAI) determines the transpiration, the interception and absorption rates of solar radiation by vegetation (Monteith & Unsworth, 2008). LAI is an important variable in numerous land surface models (Jarlan et al., 2008; Oleson & Bonan, 2000; Parton et al., 1996; van den Hurk et al., 2003). Assimilation of LAI derived from remote sensing data into crop models has been shown to improve biomass and yield estimation (Dente et al., 2008; Fang et al., 2008; Guérif & Duke, 2000; Prevot et al., 2003). For the data assimilation approaches, high resolution multi-temporal remote sensing data is advantageous, as spatial variability captured by remote sensing data is useful for adjusting crop and soil properties taking into account local conditions (Guérif & Duke, 2000), and multiple remote sensing observations over a given growing season are better for the optimization or adjustment procedures than a single observation at the peak development stage (Fang et al., 2008).

Several approaches have been developed to estimate LAI using optical remote sensing data. For instance, a three-dimensional radiative transfer model can be inverted to generate global LAI products from MODIS data using a lookup table (Knyazikhin et al., 1998). Neural network approaches have been developed to generate canopy biophysical products from top-of-canopy (TOC) reflectance measurements, such as the algorithms used to generate LAI products from SPOT-VEGETATION (Baret et al., 2007) or MERIS (Bacour et al., 2006) data. The neural network is usually trained with a spectral database built by running leaf-canopy radiative transfer models. Although these approaches are based on physical models and have the capacity to

* Corresponding author. Tel.: +1 613 759 1452; fax: +1 613 759 1724.
E-mail address: Elizabeth.pattey@agr.gc.ca (E. Pattey).

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doi:10.1016/j.rse.2012.04.002

incorporate all the radiometric measurements available from a sensor, a few studies have showed that the accuracy of the derived products may not meet application requirements in specific cases (Canisius et al., 2010; Weiss et al., 2007). For instance, crop LAI was found to be significantly underestimated by the MODIS LAI product, and this could not be completely explained by biome misclassification and atmospheric perturbation (Yang et al., 2007). It is suggested that a standardized regional network is needed for in situ LAI measurement to calibrate the MERIS LAI products (Canisius et al., 2010; Morisette et al., 2006). Other approaches consist in developing simple regression models using in situ LAI measurements or LAI products derived from well-calibrated higher resolution remote sensing data (Fernandes et al., 2003). The Partial Least Squares Regression (PLSR) is one of such an approach (Arenas-Garcia & Camps-Valls, 2008; Hansen & Schjoerring, 2003), in which LAI is estimated from a set of features using multiple regression analysis. The feature set is extracted from the original radiometric measurements through principal component analysis. Although information in all the spectral bands is used in this approach, it is not straightforward to interpret the physical meaning of the extracted features. Vegetation indices combining reflectance from a few spectral bands have been related with various biophysical descriptors and have been used for LAI estimation. This approach provides baseline LAI products that meet the requirements of a variety of studies (Chen et al., 2002; Fassnacht et al., 1997; Fernandes et al., 2003; Haboudane et al., 2004).

Most vegetation indices used for green LAI estimation combine reflectance in the visible and near infrared (NIR) wavelengths. Reflectance in the visible region helps to control the perturbation effect of background soil, whereas reflectance in the NIR domain allows for a large dynamic range of detection (Pinty et al., 2009). The normalized difference vegetation index (NDVI) is by far the most widely used index in the literature; however, it is sensitive to soil reflectance and saturates at a relatively low LAI level. Substantial efforts have been made to minimize soil effects, such as the development of the soil adjusted vegetation index (SAVI; Huete, 1988), the optimized SAVI (Rondeaux et al., 1996) and the Modified SAVI (Qi et al., 1994). Initiatives have also been devoted to improving the sensitivity of a vegetation index at high LAI and to reducing atmospheric perturbation, such as the three-band and the two-band enhanced vegetation index (EVI; Huete et al., 2002; Jiang et al., 2008). Haboudane et al. (2004) developed the modified triangular vegetation index (MTVI2), which combines hyperspectral reflectance in the NIR, red and green wavelengths in order to reduce perturbation from leaf chlorophyll content variation for crop green LAI estimation. In addition to suppressing chlorophyll effects, MTVI2 also incorporates an adjustment mechanism to reduce background soil effect. There is a need for research to evaluate the performance of these vegetation indices in deriving LAI products over multiple years within a reasonably large agricultural region. Especially, as MTVI2 was developed for hyperspectral data, it is interesting to assess its performance on multispectral data and compare it with other vegetation indices.

Vegetation indices are dependent not only on green LAI but also on other factors. First, spectral reflectance at the canopy level is dependent on leaf optical properties, which are determined by leaf mesophyll structure, chlorophyll content, dry mass and water content (Jacquemoud & Baret, 1990). Second, radiation penetrates through vegetation layer and interacts with background soil; therefore soil reflectance also contributes to TOC reflectance. Third, atmospheric constituents interact with radiation and modulate the at-sensor radiance. If the variability of atmospheric constituents cannot be adequately accounted for in atmospheric correction, the uncertainty will be carried over to canopy reflectance retrieval. Fourth, in addition to LAI, leaf inclination, clumping and solar angle also determine radiation interception and absorption; therefore, they also affect vegetation spectral reflectance. These uncertainties determine that canopy biophysical parameter retrieval is an ill-posed problem (Combal et al., 2003). Approaches using contextual information, such as temporal signature and spatial constraints (Atzberger, 2004; Dorigo et al., 2009; Koetz et al., 2005; Lauvernet et al., 2008), have been developed to address this issue. The use of in situ LAI measurements in a regression model potentially reduces uncertainties and improves LAI estimation. It is thus desirable to evaluate the capability of vegetation indices in mapping crop LAI at a regional scale.

The objectives of this study were to 1) evaluate the use of vegetation indices for crop green LAI estimation over multiple years and at a regional scale; 2) assess the uncertainty induced by factors other than green LAI, and evaluate the relative impact of these factors in LAI estimation; and 3) assess the influence of spectral resolution on MTVI2 for LAI estimation. High spatial resolution optical remote sensing data have been made available through various orbital satellites. The Landsat program, in particular, has provided high resolution observations of the Earth's surface on a continuous basis since 1972. This long-term earth observation program will be merged with the Landsat Data Continuity Mission (LDCM) in the near future (Wulder et al., 2008). Thus, data acquired by the Landsat series satellites represent an essential resource, not only for retrospective purposes, but also for prospective studies at a local scale. In the near future, the European Space Agency's Sentinel-2 satellites will provide operational earth observation data with high spatial resolution and short revisiting cycle. Thus, this study will provide assessment on using the Landsat data and implications on the use of Sentinel-2 data in similar application cases. The assessment of MTVI2 also provides a prospective study on the use of hyperspectral data in anticipatory to future satellite hyperspectral missions, such as the German EnMAP and NASA's HyspIRI missions.

2. Material and methods

2.1. Remote sensing data

In order to generate high resolution LAI product to support research studies on remote sensing data assimilation into crop models, we collected all cloud-free Landsat-5 and Landsat-7 images over an experimental farm (~4 by 4 km) in Ottawa, Ontario, covering the growing seasons from 1999 to 2006. The images were retrieved from the Landsat data archives of the United States Geological Survey (USGS). Table 1 lists the number of images available for the 8 growing seasons. Landsat-7 images after the failure of Scan Line Correction were not collected, as the study site is located to the edge of the swath where data missing is significant. The study area is covered twice every 16 days, either by path/row 15/29, or path/row 16/28 7 days later. However, frequent cloudy conditions reduce the numbers of images that can be exploited. In all, 64 images with suitable quality were available for the 8 growing seasons.

The Landsat images retrieved from the USGS collection were geometrically corrected with satisfactory accuracy. Radiometric calibration

Table 1
Number of Landsat-5/7 images and field LAI sampling sites.

Year	Images[a]	Number of ground LAI sampling sites			
		Corn	Soybean	Wheat	Total
1999	6 (5)		6		6
2000	7 (6)	8			8
2001	8 (4)	13	6	14	33
2002	9 (7)	7			7
2003	9			3	3
2004[b]	9				
2005	7			2	2
2006	9	19			19
Total	64 (22)	47	12	19	78

[a] The total number of Landsat-5 TM and Landsat-7 ETM+ images, with the number of ETM+ images acquired before the failure of the Scan Line Correction in parentheses.
[b] In 2004, canola ground LAI was measured.